A FUZZY-NEURO SCHEME FOR FAULT DIAGNOSIS AND LIFE CONSUMPTION OF ROTORDYNAMIC SYSTEMS

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Abstract: An intelligent health monitor for rotating machinery is presented that integrates proven neural network and fuzzy logic technologies with rotordynamic, finite-element modeling. A rotor demonstration rig is used as a proof of concept tool. The approach integrates rotor shaft vibration measurements with detailed, rotordynamic, finite-element models through a fuzzy-neuro scheme which is specifically developed to respond to the rotor system being monitored. The advantage of this approach over current methods lies in the use of a neural network classifier and fuzzy logic reasoning algorithms. The real-time neural network is trained to contain the knowledge of a detailed finite-element model whose results are integrated with system measurements to produce accurate machine fault diagnostics and component stress predictions. The availabilty of these real-time stresses allows for critical component life estimates to be calculated during machine operation. Fuzzy logic is implemented to overcome system measurements uncertainties, provide machine fault severity information, and make informed decisions about maintenance actions that should be performed based on operator experience.

Key Words: Artificial Intelligence, Diagnostics, Condition Monitoring, Neural Networks, Fuzzy Logic, Rotor Dynamics, Finite Element Models, Real-Time, Health Monitoring.

Introduction: Over the last several years, the practical strengths and weaknesses of applying neural networks and fuzzy logic in real-world condition monitoring systems have become more clear. Namely, pattern recognition based neural networks do not work very well on inconsistent or changing failure modes that many different types of machines exhibit (turbo-machinery in particular). In addition, the system specific training data required for training a neural network to recognize common machinery faults is typically not available. Also, fuzzy logic schemes do not lend themselves easily to modeling complex, nonlinear systems due to the large rulebases that would need to be generated for proper accuracy. However, by recognizing the *practical* capabilities of each of these technologies, a system developer can judiciously implement the individual technical benefits of each to meet the demands of more reliable and accurate condition health monitoring.

Utilizing the system modeling strengths of neural networks, machinery component finite element models can be represented with neural networks. By training a neural network from parametric analysis performed with a FE model, critical component stresses can be predicted in real time. These real-time, monitored stresses can then be used in LCF/HCF fatigue life algorithms to monitor critical component life damage as the machine is operating. In addition, the strengths of fuzzy logic can be utilized to minimize the effects of measurement uncertainties and system non-linearities. Confirmed fault diagnosis (based on operator experiences) and fault severity monitoring is also easily accomplished with fuzzy logic algorithms.

This paper demonstrates a **fuzzy-neuro** system (i.e. a system the implements both fuzzy logic and neural networks) for improving the present state-of-art in machinery health monitoring by increasing the effectiveness and reliability of mechanical diagnostics and component life monitoring. Specifically, a trained network is used to process relevant system sensor data in order to make informed decisions on a rotor's mechanical health and monitor critical rotor stresses. The real-time cyclic stresses are then analyzed by a damage accumulation algorithm to report a remaining component life estimate. A fuzzy logic scheme is developed to monitor the severity of the diagnosed fault, check the diagnosis performed by the neural network, and report on the maintenance action required to correct the fault.

Rotor Demonstration Rig: A rotor rig was constructed to demonstrate the concepts proposed in this paper on actual hardware. The demonstration rig was designed to be versatile enough to duplicate various vibration-producing phenomena found in all type of rotating systems. Many different types of vibration related characteristics were created and measured by changing rotor speed, degree of unbalance, degree of misalignment, shaft rub, and rotor bearing clearances. The resulting dynamic characteristics are measured with proximity probes and/or accelerometers and are processed with a multi-channel dynamic signal analyzer. The rotor configuration utilized in this paper is shown in Figure 1.

Two roller bearings support the motor armature, while four, oil impregnated, bronze sleeve bearings are positioned between the various couplings and disks. A solid 36" aluminum base with adjustable bearing pedestal locations and rubber isolation feet provide sufficient rigidity to the rotor configuration. Motor speed control is maintained with a proportional speed feedback algorithm, with speed sensed by a dedicated proximity probe and toothed wheel.

Seeded faults were introduced into the rotor demonstration system by applying mass unbalances to the disks, misalignment across the rigid coupling, loosening the bearing pedestals, and installing pre-worn bearings. Under each of these conditions, measurements were obtained from each of four proximity probes to determine the magnitude and phase of each transducer with respect to the reference key phaser. The specific magnitude and phase measurements were logged into a database and used in the neural network training procedure.

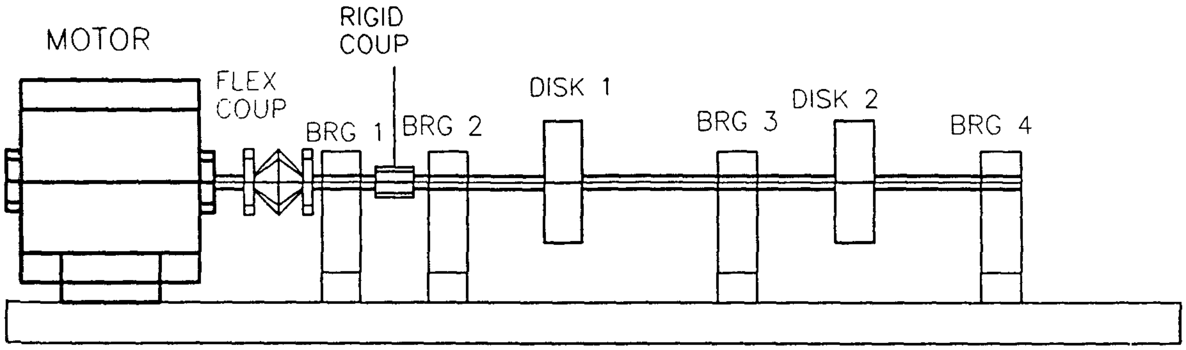

Figure 1 Rotor Demonstration Rig

Rotor Dynamics Finite Element Model: A detailed finite element model of the rotor demonstration system was developed and correlated with measured experimental data. This computer model was used to simulate rotor operation and to train the neural network classifiers. In particular, the network was trained from the model to determine dynamic stresses and forces in critical mechanical components. Figure 2 illustrates the first critical mode associated with the finite element model. In addition, the model predicts overall rotor vibratory characteristics as well as local vibratory stress levels. The real value in having a finite element model based diagnostic system is that it provides a very accurate picture of the rotor stress distribution and reaction forces. These stresses and forces are the cause of many of the component failures in the rotor, bearings, seals, etc. With the rotating shaft component stresses predicted, an automated life analysis algorithm will be able to determine what the expected component life will be with any damage condition.

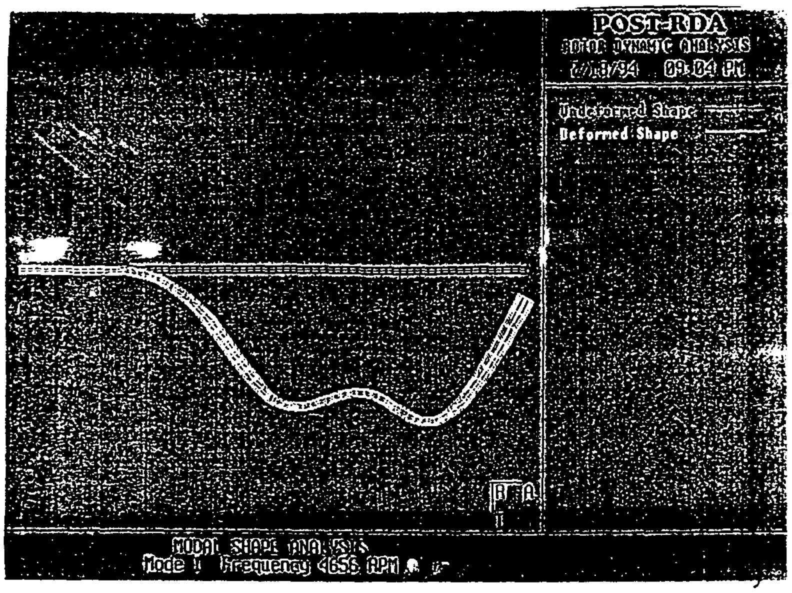

Figure 2 Calculated First Critical Rotor Mode

Fuzzy-Neuro System Development: The **fuzzy-neuro** system architecture developed in this paper provided for efficient measurement data processing and resulted in confirmed diagnoses of the rotor mechanical faults and rotor shaft component life estimation. A block diagram of the developed system architecture is given in Figure 3. In this figure, the "Diagnostics" block represents the neural network classifier, the "Fault Severity" and "Maintenance" blocks represent the fuzzy logic membership functions and rulebases, and the "Life Module" block contains the life accumulation algorithm. The system was developed as a stand-alone application comprising multiple functions and a single executable file to assist system testing and verification.

The complete diagnostic system shown in Figure 3 consisted of 6 transducer inputs and 4 diagnostic related outputs. The system inputs included four bearing vibration signals, relative phase across the shaft coupling, and rotor speed. A neural network was used to map specific one per-rev rotor responses to corresponding unbalances or misalignments as well as predict shaft stresses based on FE model training. The outputs of the "Diagnostic" neural network predict the probability of having an unbalance in balancing plane 1, balancing plane 2, or a misalignment across the coupling. The "virtual sensor" outputs of the network predict the stresses at two critical locations on the shaft. These real-time shaft stress are transferred simultaneously with the rotor speed measurements to the component "Life" module. The component life module continuously computes and updates the remaining fatigue life associated with the maximum cyclic shaft stress monitored during the current start/stop cycle.

The bearing vibration measurements are also processed by a "Fault Severity" fuzzy logic module. Processing the raw measurement data allows the fault severity module to perform a check on the network diagnosis as well as performing its standard function of determining the severity of a diagnosed fault. The outputs of this "fuzzy" module indicate the severity of an unbalance condition or coupling misalignment in linguistic terms such as "severity is minor", "severity is moderate", etc.

The final module entitled "Maintenance" accepts data from the output of Diagnostic" neural network and "Fault Severity" fuzzy logic. By examining the diagnosed fault and associated fault severity, this module recommends specific maintenance actions that should be performed by the operator in linguistic terms. For example, if a fault is diagnosed as an unbalance condition in plane 2 with a severity level of minor, the "Maintenance" module would prompt the operator to monitor this situation over the next several days to see if the condition is worsening. If time passes and the unbalance severity worsens to a moderate level, then the maintenance action might be to "monitor condition very closely". Finally, if the severity continues to worsen, then a "shut down and balance plane 2" message would be given to the operator. The complete fuzzy-neuro system comprised of the diagnostic, fault severity, life, and maintenance modules is described next.

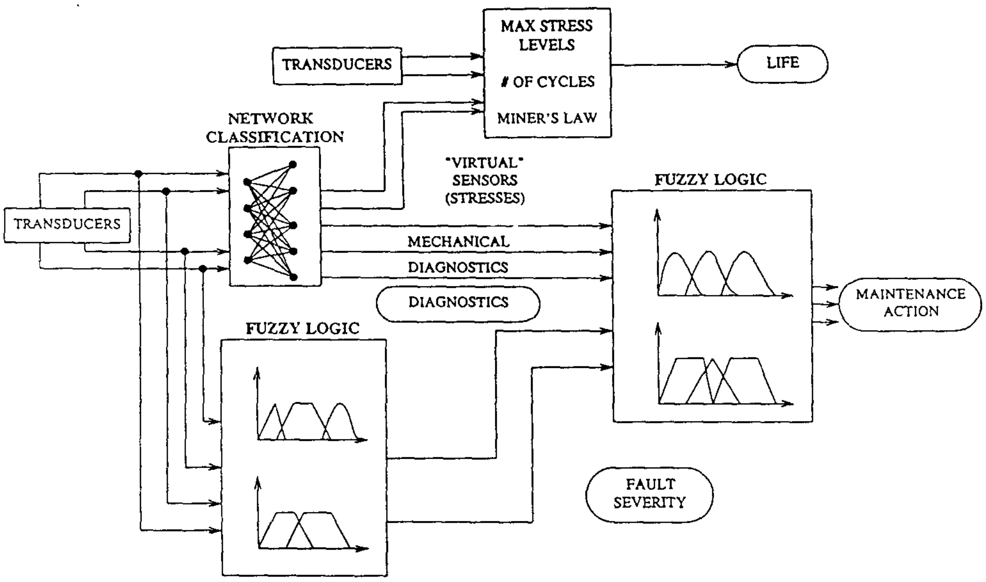

Figure 3 System Block Diagram

Neural Network Module: The neural network configuration illustrated in Figure 4 utilizes four bearing vibration input measurements and relative phase information across the flexible coupling to yield 5 input nodes to the network. One hidden layer, consisting of 10 nodes, is used to increase the "flexibility" of the network. Hidden layers, when used properly, can provide more accurate correlation between complex, linear and nonlinear training patterns. The output layer of the network consists of 5 nodes.

The first three output nodes of this network configuration diagnose the gross fault condition as either; 1.) an unbalance in balance plane 1, 2.) an unbalance in balance plane 2, or 3.) a misalignment across the coupling. The remaining two output nodes give important "virtual sensing" information about shaft stresses at two critical locations.

Virtual sensing refers to indirectly measuring a parameter such as shaft stress by matching patterns of directly sensed data (such as bearing displacement) with a finite element model to yield an accurate measurement of the unmeasured parameter. For the demonstration rotor system, the shaft bending stresses are calculated using a detailed finite-element model of the rotor for particular rotor conditions. The neural network is then trained to recognize the sensed patterns and relate them to the values calculated from the model. The result is a neural network (trained from measurements and FE model) that is capable of "virtually" sensing stresses on particular components in real time without actually having installed strain gages on-board.

Training the neural network involved evaluating the weights and thresholds of the numerous interconnections between the input and output layers. This was conducted utilizing a supervised training procedure. The supervised training technique specifies what target outputs should result from an input pattern. The neural network variables (weights and thresholds) are then self adjusted to generate that target output. The training procedure utilized a back propagation least-square error approach to achieve the desirable network accuracy. Network training was based on experimental

case histories and analytically derived input/output pairs resulting from the rotor dynamics computer model.

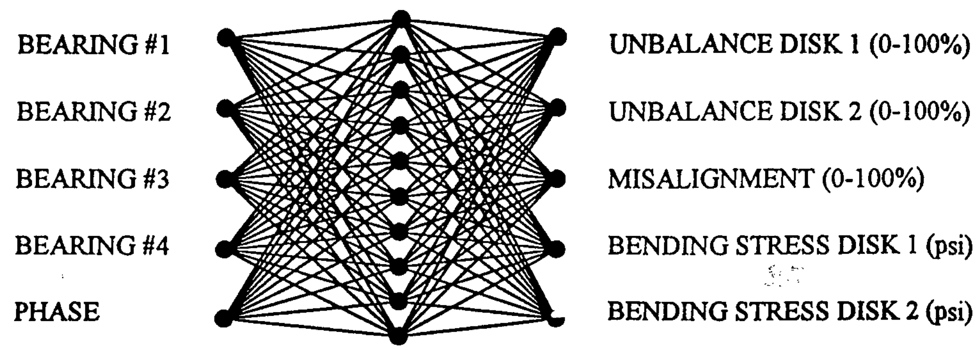

Figure 4 Neural Network Architecture

The network architecture was trained with 50 input/output training patterns devised from both experimental measurements and the finite element model analysis. The training patterns of the network database focused on diagnosing mass unbalance conditions, coupling misalignment, and shaft stresses. As an example, experimental data was collected from the rig to train the neural network to distinguish the differences between misalignment and an unbalance condition. Both of these conditions exhibit similar one/rev vibration characteristics. Phase angle measurements were obviously very important for the network to make this distinction.

The rotordynamics finite element model was exercised extensively with numerous unbalance force and shaft misalignment conditions. The results from each run of the finite element model yielded steady-state shaft bending stresses for each of these forcing conditions. The results were then used in conjunction with the measured data to build the training pattern database.

Fuzzy Logic Modules: Two fuzzy logic modules were developed for the rotor health monitoring system. First, a "Fault Severity" fuzzy logic scheme was introduced to monitor the level of risk a particular fault is producing. This severity level is calculated from the raw transducer measurements and therefore acts as a check for the neural network diagnosis. The outputs of the fault severity module are combined with the outputs of the diagnostic network to form the six inputs to the "Maintenance" module. The maintenance module examines any diagnosed fault and corresponding level of severity to determine the best action to be performed by the machine operators.

The "Fault Severity" module utilizes four bearing vibration inputs to determine three fault severity outputs. Fuzzy logic membership functions and corresponding rulebase were developed for each input and output variable. An example of an output variable membership function is given in Figure 5.

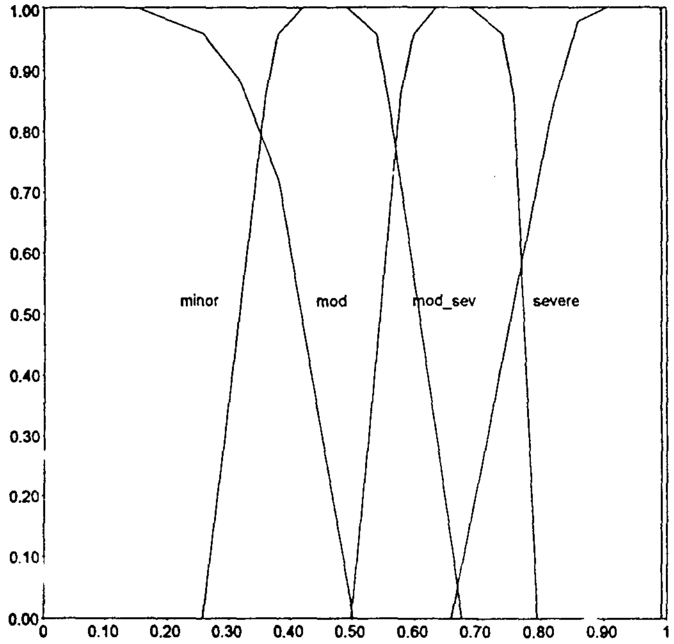

Figure 5 Fault Severity Membership Function

The fault severity membership functions were developed based on the experienced gained from operating the rotor demonstration rig. For example, the vibration amplitudes measured near bearing 1 were consistently higher than the levels measured near bearing 4. Therefore, the corresponding membership functions must represent this knowledge accurately. The rulebase developed from the vibration patterns exhibited from the unbalance and misalignment seeded faults were accurately represented with only 16 rules. A representative rule would be; (IF bearing_1 IS high) AND (bearing_2 IS low OR bearing_2 IS medium_low), THEN coupling misalignment severity is severe. The combination of the input/output membership functions and rulebase make up the knowledge of the fault severity module. A product-sum fuzzy inference method was used to scale and combine the membership functions, while the centroid technique was used for defuzzification.

The maintenance fuzzy logic module was developed similarly to the fault severity module except six input and three output membership functions were needed. The rulebase consisted of 22 rules that primarily examined the relationship between a diagnosed fault and corresponding severity level. An example rule is; IF unbalance_plane_2 IS high AND unbalance_2_severity is severe, THEN shut down balance plane 2. Maintenance module outputs for a plane 1 unbalance, plane 2 unbalance, or coupling misalignment are described as either "operational", "to be monitored", "to be monitored closely", or "shut down".

Component Life Module: A fatigue life algorithm was developed that utilizes the virtually sensed shaft stresses as a basis for computing fatigue initiation life. The algorithm estimates the amount of time to crack initiation, with crack propagation not being considered. Neuber's Rule is used to compute the true stress and strain in the crack initiation region. Morrow's Method is used to

incorporate the mean stress effects in the life calculations, which are based on strain-amplitude and the number of reversals. Miner's Law computes the cumulative fatigue damage.

Strain-Life Equation: The local strain approach was used to calculate the total strain, ε, including elastic and plastic components, from the given stress state and the fatigue properties of material:

$$\varepsilon = (\sigma'_f - \sigma_o)\,(2N_f)^b / E + \varepsilon'_f (2N_f)^c$$

where E is the elastic modulus, σ_o is the true mean stress or the true steady stress, and N_f is the number of cycles required for crack initiation. In the right hand side of the equation, the first term represents an elastic strain and the second term represents a plastic strain. This equation is the foundation for the cyclic strain-based approach to fatigue prediction and is usually called the strain-life equation.

Cycle Counting and Cumulative Damage: Under spectral loading, the dynamic strain conditions at critical locations of a component may have very complex waveforms. Several procedures exist to deal with this situation, of which, the Rainflow cycle counting procedure is well known. Simply stated, this procedure consists of dividing the complex waveform into a sequence of simple cycles, and then counting the number of strain cycles within a given strain range. The resulting number is then compared with the tested fatigue life of the material at this strain level to determine the degree of incremental damage. The best known cumulative damage assessment procedure is Miner's Law, which states that the cumulative damage is equal to the sum of the incremental damage at the various strain ranges.

$$\sum \frac{n_i}{N_i} = 1;$$

this procedure is utilized in this fatigue life algorithm. The number of cycles n_i occurring at a given strain level is first computed from the Rainflow cycle counting procedure. The number of cycles to failure at each strain level, N_i , is based on test sample data and adjusted for mean stress effects. This is obtained from the strain-life equation. The portion of damage at this strain level becomes n_i/N_i. The summation sign in the Miner's Law equation indicates that the cumulative damage is the sum of damage portion due to all existing strain levels. Accordingly, the crack initiation is expected to occur when the cumulative damage is equal to or greater than unity.

System Verification and Test Results: Several parametric tests were conducted involving seeded fault conditions applied to the demonstration rotor system. Accuracy of the neural network diagnostic outputs, fuzzy logic module outputs, and overall system outputs were compared with the "true" seeded fault condition. As an example, if a "minor" mass unbalance was imposed on disk #1, then the network diagnostic output should ideally respond "100 percent chance of unbalance on disk #1", the fault severity module respond as "severity is minor", and the overall system output should respond "monitor disk #1 unbalance.

To convey the diagnostic and life monitoring testing results most completely, a worsening unbalance condition was subjected to balancing plane 1 of the demo rotor rig. At first, sensor measurements were acquired from the rig under the absence of the unbalance condition. Next, data was acquired after a "minor" unbalance of 0.05 ounce-inches was applied to disk 1. Consecutive, unbalance magnitude increases were applied to disk 1 until a "severe" unbalance of 0.25 ounce-inches was reached. A sample of the output data file showing four discrete testing results is given in Figure 6.

The four discrete system outputs resulted from four sets of measurement data acquired from the rotor rig over a large time frame. During actual monitoring system operation, a system output describing unbalance, misalignment, and shaft life status is provided for every set of transducer measurements acquired. Reported system monitoring results can be provided at user specified intervals.

Several seeded fault conditions were examined similar to the one described above. The rotor monitoring system was capable of accurately tracking a worsening rotor fault condition as well as monitor remaining life of the rotor shaft. The system "fuzzy" outputs describe to the machine operator what steps he/she should take as a condition worsens.

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----- Life Module Results:  Stress 1 = 6.787332    Stress 2 = 7.724948
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Coupling Alignment Is Operational
Balancing Plane 1 Is Operational
Balancing Plane 2 Is Operational
Remaining Shaft Life = 0.000000e+00  years
-----
----- Life Module Results:  Stress 1 = 86.611595   Stress 2 = 18.802980
-----
Coupling Alignment Is Operational
Balancing Plane 1 Should Be Monitored
Balancing Plane 2 Is Operational
Remaining Shaft Life = 3.784470e+31  years
-----
----- Life Module Results:  Stress 1 = 159.930435   Stress 2 = 38.713123
-----
Coupling Alignment Is Operational
Balancing Plane 1 Should Be Monitored Closely
Balancing Plane 2 Is Operational
Remaining Shaft Life = 7.918761e+16  years
-----
----- Life Module Results:  Stress 1 = 263.891205   Stress 2 = 61.637596
-----
Coupling Alignment Is Operational
Balancing Plane 1 Should Be Re-Balanced ASAP
Balancing Plane 2 Is Operational
Remaining Shaft Life = 2.503154e+15  years
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Figure 6 System Testing Results

Conclusions: A fuzzy-neuro machine health monitor that performs both mechanical diagnostics and component life prediction was demonstrated with the use of a miniaturized rotor system. The rotor system was subjected to mechanical fault scenarios including; mass unbalances and coupling misalignments in order to examine the benefits of utilizing fuzzy-neuro technologies for monitoring rotating machinery. A neural network classifier was able to accurately diagnose mechanical faults based on the associated vibration signatures measured from the desktop system. Fuzzy logic was used to determine fault severity levels and make decisions on required maintenance action. In addition, component life accumulation was monitored based on the diagnostic outputs provided by the neural network

The concept of training neural network classifiers with both rotor system measurements and detailed finite element models is highlighted as a significant advancement in condition monitoring applications. The rotor dynamics finite element model was used to train the diagnostic network to recognize fault patterns and their resulting effect on shaft stresses. This real-time, "virtual" sensing of shaft stresses allows for component life monitoring to be achieved in real-time. In other words, the ability of the neural networks to recognize particular vibration signatures and correlate them with associated shaft stresses is of particular significance.

Finally, through the use of fuzzy logic, the diagnostic system provided the necessary robustness to measurement noise and changing failure mode vibration patterns. In addition, by processing the raw transducer inputs in both the diagnostic neural network and fuzzy logic scheme simultaneously, increased accuracy of the diagnosed faults and corresponding corrective action recommendations was accomplished while preserving the real-time requirement of the system.

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